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Model-based Control of a Glass Melting Furnace

Riccardo Bacci di Capaci [*,****] **Leonardo Musi** [**]
Alberto Landi [**] **Luca Sani** [***] **Sami Barmada** [***]

[*] *Department of Civil and Industrial Engineering, University of Pisa, Italy*
[**] *Department of Information Engineering, University of Pisa, Italy*
[***] *Department of Energy, Systems, Land and Construction Engineering, University of Pisa, Italy*
[****] *Corresponding author: riccardo.bacci@unipi.it*

Abstract: This paper derives practical dynamic models for the glass industrial manufacturing process to be then included in model-based control solutions. In particular, the first section of the plant, that is, the glass melting furnace is investigated: silica sand and recovered glass are used as raw materials, and through methane and oxygen combustion melt glass is obtained which is then sent to the condition and final processing sections. Routine input-output data are employed to identify models of the furnace, including the loading machine, the fan, and the gas burners. Models of the various control valves are also identified, and finally, the parameters for the existing PI/PID controllers are estimated. A decentralized scheme comprised of SISO controllers and a centralized architecture with a model predictive controller (MPC) are designed and compared in a simulation scenario. The MPC solution guarantees higher performance with respect to the decentralized scheme by reaching a good trade-off between velocity of response and reduced oscillations.

Keywords: Glass melting furnace, model predictive control, system identification, data-driven models

1. INTRODUCTION

Modern glass production process is carried out on a large scale, by obtaining finished products of high quality with different shapes and properties. To this aim, large and complex plants are employed which require significant amounts of energy and utilities and also fine regulation. The typical glass production process can be summarized as follows: the refined mixture of silica sand is heated in an insulated melting furnace to a temperature above 1200°C; the molten glass is hence cooled in the conditioning section to around 800°C; then, within the forming process, the shape of the finished products is obtained. Finally, once formed, the glass is cooled and annealed to relieve internal stresses thanks to a partial reorganization of the molecules (Axinte, 2011).

Glass melting furnaces can be classified into: classic combustion furnaces, where only the heat generated by combustion is used; electric furnaces, where the heat is generated by the Joule effect exploiting the resistance property of the glass, and mixed furnaces (Horn Glass Industry, 2023). Fuel furnaces are further divided according to their structure and the comburent employed: recuperative, regenerative, and oxy-fuel furnaces are the most common types. The first two, which use air as a comburent, require an efficient system for exhaust fume heat recovery. In recuperative furnaces, a continuous recovery is achieved with a double shell heat exchanger between fumes and comburent. In regenerative furnaces, two towers with a large thermal capacity act as elements of heat accumulation and release in the different process phases. Finally, the oxy-fuel furnaces use almost pure oxygen as a comburent and do not exploit exhaust fumes, since the flow rate is reduced due to the lack of nitrogen.

Different approaches have been proposed in the literature for the modeling and consequent control of glass melting furnaces (Havel, 2006). As in many other industrial fields, these methods belong to two large families, based on the nature of the model: first principles and data-driven methods. As an example of the first type, Sardeshpande et al. (2007) developed a model using mass and energy balances, heat loss equations for the different zones, and empirical equations based on operating practices. Later, Choudhary et al. (2010) reviewed the scientific and engineering principles and practices involved in the modeling of flow and heat transfer phenomena in industrial-scale glass melting, delivery, and forming processes. However, first principles models, despite being very accurate solutions, tend to be impractical. To this aim, Auchet et al. (2008) proposed a simplified first-principles approach made to lower the computational demand and then implement an MPC. Pure data-driven models, which identify a dynamic model starting from a set of real data, i.e. samples of the measured input/output variables of interest, prove to be more useful and are suited for control design. Moon and Lee (2000) identified simple First-Order-Plus-Dead-Time models by using process experimental data to derive a conventional multi-loop control architecture. Rajarathi-

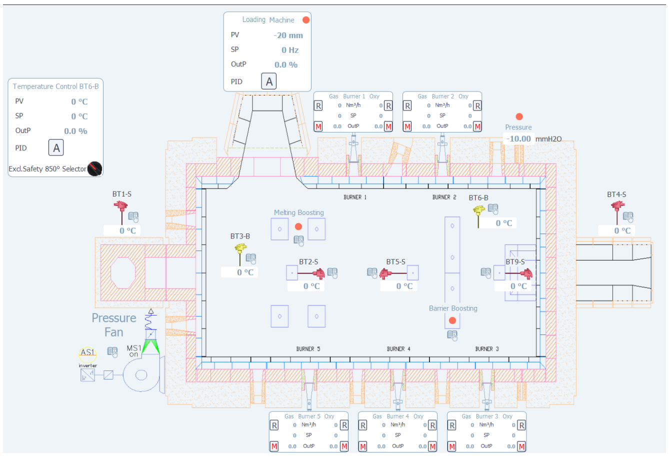

Fig. 1. Synoptic of the considered glass melting furnace.

nam et al. (2016) investigated standard genetic algorithms to identify control-oriented models which are subsequently used for controller optimization.

The objective of this work is thus to derive a set of practical data-driven linear models for an industrial glass melting furnace. The obtained models are used for the design of suitable model-based controllers to be then implemented in the plant PLC. The remainder of the paper is briefly reported. Section 2 describes the case study analyzed for the scope, while Section 3 illustrates the phases of the adopted methodology; the different identified models are described in Section 4 and the relative control schemes are designed and tested in simulation within Section 5. Finally, conclusions are drawn in Section 6.

2. THE CASE STUDY

Here below the description of the considered glass furnace is given with details of the corresponding control system.

2.1 The physical system

The system under investigation is a glass container production plant of FaloriTech - Pavisa Group, located in Mexico. The plant, similarly to others of its type, can be divided into three main sections: i) the melting furnace: where the raw materials are converted into molten glass; ii) the conditioning bath: where the molten glass is slowly cooled to eliminate bubbles and imperfections; iii) the finishing processing: where the final glass containers are obtained. The study focused on the modeling and control of the melting furnace, a multivariable section that requires fine regulation. The considered furnace is of the oxy-gas type, thus employing methane gas as fuel and pure oxygen as comburent (see the synoptic of Figure 1).

The furnace presents two main areas, the combustion chamber for the gas reaction with burners and the underlying glass melting bath; these areas are not physically separated but continuously exchange heat by radiation and conduction phenomena. To avoid significant structure deformations and heat losses, the furnace presents a layer structure, that is, the internal walls are of compact and resistant material to heat and mechanical stress, while the external walls are extremely insulating. A loading machine feeds the furnace with silica sand and other chemical components, such as sodium and calcium, but also recycled glass. These materials move horizontally through the furnace with inclined floor, mainly due to the gravity effect and secondly due to the convective motions generated by temperature gradients. Five gas burners and an auxiliary electrical system heat uniformly the molten glass. Methane and oxygen, once appropriately preheated, are mixed with an established flow rate ratio. The gas flow rates are not independent, but governed by a specific distribution logic. To get the desired temperature profile, the total gas flow rate is set and then split between burners with constant ratios over time. As an additional heating system, an electric boosting is installed: a series of four vertical electrodes in molybdenum is used and a suitable potential difference is imposed. The glass, moving between electrodes at different potentials, produces electrical resistance generating current and hence heat for the Joule effect. An air jet pushed by an electric fan, placed at the furnace outlet, controls the overall combustion chamber pressure. This generates an “air curtain” which horizontally cuts the outlet to the chimney and regulates the flow rate of fumes and thus the overall pressure.

As sensors, five thermocouples are installed: three soil instruments (BT2, BT5, BT9) for the temperature of the refractory pavement just below the molten glass; two sensors (BT3, BT6) for the combustion chamber, that is, for the gas phase. Instruments are enclosed in a cage of thermally insulating protective material to allow reliable measurements over long periods. The registered value does not instantly correspond to the actual glass temperature, since the heat needs to propagate through the cage before reaching the thermocouple. A little delay between the measured and the actual temperature is thus observed. This time delay could be introduced in the overall transfer function between the methane/oxygen flow rates and the measured temperatures, but its size can be well-neglected compared to the main furnace time constant. Moreover, critical sensors are installed for the gas phase pressure and for the molten glass level, which is obtained by a mechanical tip device. Both are relative measures with respect to a reference value, that is, the atmospheric pressure and an optimal zero level. Finally, ten flow sensors measure the inlet flow rates of methane and oxygen.

2.2 The control system

The overall control architecture of the melting furnace is comprised of several decentralized PI/PID controllers, as shown in Figure 2. The primary temperature control (TC) operates in cascade mode over ten flow rate controllers (FC). This loop sets the output of the TC based on the error between the temperature registered by the BT6 and the corresponding setpoint, typically around 1480-1490°C. The setpoint of the total methane flow rate is proportional to the TC output by a constant ratio ($R = 5$).

The total flow rate is subsequently split according to the distribution logic: in particular, 22% is assigned to burners 1, 2, and 4, while burners 3 and 5 are assigned with 16% and 18%, respectively. The control architecture regulates also the desired ratios between the oxygen and methane volumetric flow rates, which is $V_O = 2.15 \times V_M$ for each burner. Note that the oxygen setpoint is set based on the

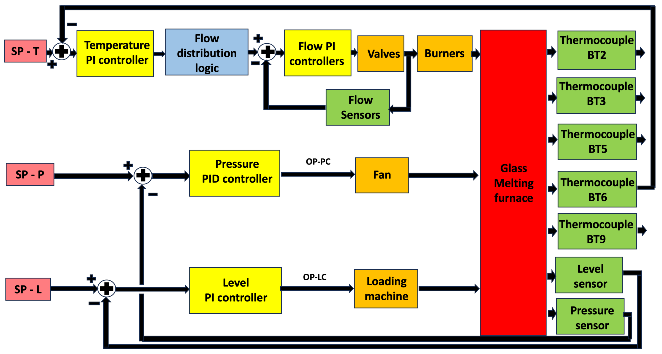

Fig. 2. Block diagram of the considered glass furnace.

measured methane instead of the corresponding setpoint, which can lead to instantaneously imperfect mixing, due to field noise and external disturbances, but this limits eventual time delay effects. Ten secondary loops thus modulate the valve opening through PI-type algorithms. The level control manipulates the loading machine velocity and then the flow rate of input raw materials. Note that due to different operational issues, such as a hard calibration of PI/PID parameters, the plant is not fully operated in automatic mode. Temperature and level are indeed usually in manual mode, while pressure control switches frequently between manual and automatic.

2.3 Quality variables and operative conditions

Once the control structure is defined, to fully characterize the plant operation, suitable quality variables and key performance indicators are specified. In particular, i) the energy consumption, ii) the inlet scrap content, and iii) the pulled-out glass (PG), i.e., the amount of molten glass cut into drops per minute, are evaluated every eight hours, i.e., at the end of each work shift.

In particular, for the first two shifts T_{sh}, from 6 to 14 and from 14 to 22, 23 melt drops (N_{dr}) are produced per minute, each with a weight of 0.935 kg. The total amount of glass produced per shift is thus equal to $m_{TOT} = PG \times N_{dr} \times t_{sh} = 0.935 \times 23 \times (8 \times 60) = 10322.4$ kg. In the last shift, from 22 to 6 of the following day, 28 drops are produced per minute, of lower weight equal to 0.850 kg, for a total amount of glass of 11424 kg. As regards consumption, total energy for boosting is equal to 800 kWh, while the volume of methane is around 1900 Nm^3. These consumption keep almost the same for the three work shifts. The percentage of scrap glass, i.e., the quantity of recycled glass in the input materials, is constantly equal to 33% of the total flow, with a small increase in the last work shift.

To sum up, we can conclude that the plant runs under very similar conditions throughout the day. Therefore, a single operative mode can be considered, thus a single dynamic model can be assumed for the molten glass furnace. Nevertheless, by a visual inspection of the registered time trends, process control performances appear very poor. In particular, persistent oscillations around the desired values of temperature are frequently observed. Therefore, the adoption of an advanced model-based control solution appears as highly desirable.

3. METHODOLOGY

To derive advanced controllers for the considered system, routine closed-loop input-output data were used to identify dynamic models. Note that plant tests were not viable due to operators' reluctance to vary input variables, so standard step tests and more informative signals, such as GBN and PRBS (Zhu, 2001), were not injected.

In particular, a model of the furnace, including the loading machine, the fan, and the 10 burners, was obtained; models of the various control valves were also identified, and finally, parameters for the existing PI/PID controllers were estimated. As a tool for identification, the well-established SYSID Toolbox of MATLAB and the open-source software SIPPY - Systems Identification Package for PYthon (Armenise et al., 2018) - were adopted. Different linear models with various structures and orders were tested and then compared by using suitable performance indices. For the sake of brevity, only some results obtained with MATLAB are reported below.

3.1 Model dimensions

The following variables have been selected to build a multi-input multi-output model of the glass melting furnace:

- 11 inputs: that is, the 10 gas volumetric flow rates at burners (B1-B5), 5 of methane (M), and 5 of oxygen (O); and the pressure controller output, that is, the input command to the fan (OP-PC).
- 7 outputs: 5 temperatures registered by 5 thermocouples (BT2, BT3, BT5, BT6, BT9) along the furnace; the combustion chamber pressure; and the molten glass level.

To identify a model for the control valves, the output of the corresponding PI controller was selected as input and the relative control variable, that is, the actual flow rate (methane or oxygen), was chosen as output. For the estimation of PI/PID controller parameters, the corresponding error between the setpoint value and control variable was used.

3.2 Data selection and preprocessing

By visual inspection, a change in one of the various inlet flow rates has a prompt effect on the temperature registered by two thermocouples (BT3, BT6) on the gas phase, while, for the other three soil temperatures, large time constants are observed. Among the 7 available datasets, each long at least 1 day of operation and with a sampling time of 5 seconds, the most 3 informative datasets were selected, that is, the ones with higher variation in the input variables. These datasets were then pre-processed, that is, further cut, filtered with a moving average method to reduce the effect of sensor noise and quantization, and finally normalized. The first 3/4 of the dataset was used for identification purposes, while the last sector was employed for model validation. Figures 3 and 4 show an example of input and output data, respectively; the beneficial effect of filtering is well visible. For the sake of space, only 3 inputs out of 11 plus the level controller output (that is, the loading machine input, OP-LC, here in manual mode) and 4 outputs out of 7 of Section 3.1 are reported.

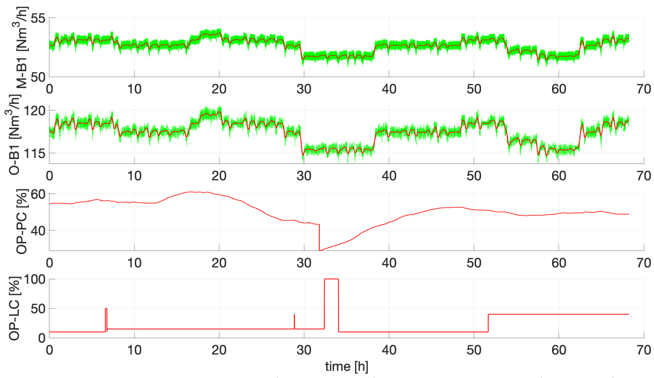

Fig. 3. Input data: raw (in green) and filtered (in red).

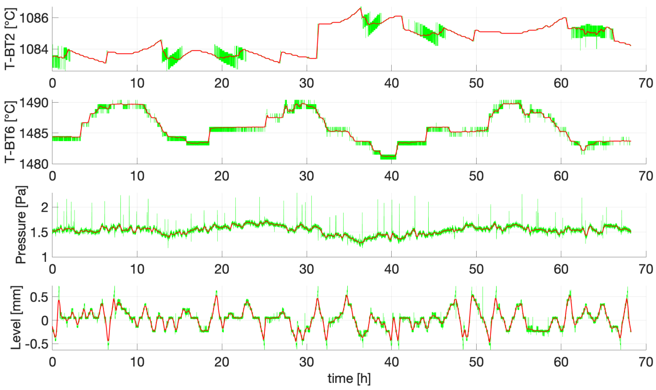

Fig. 4. Output data: raw (in green) and filtered (in red).

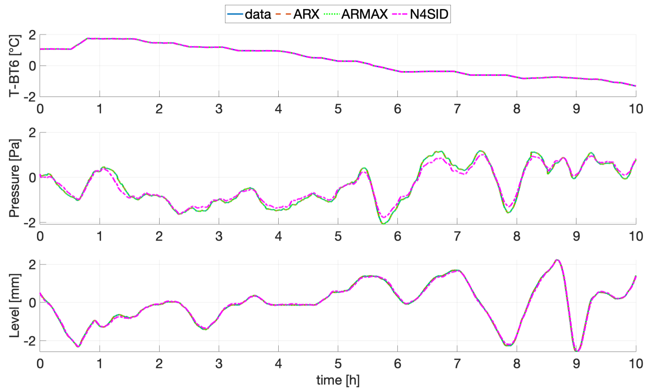

Fig. 5. Identification: original system vs. model outputs.

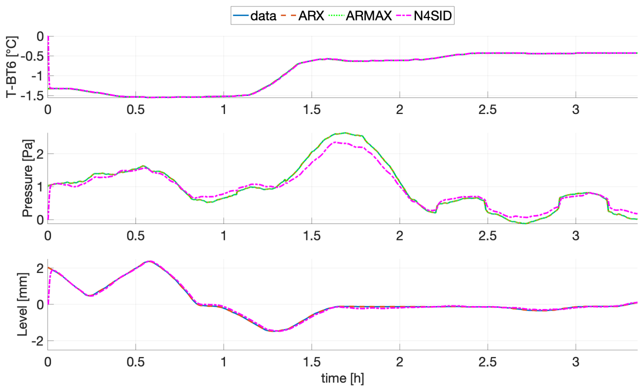

Fig. 6. Validation: original system vs. model outputs.

4. MODEL IDENTIFICATION

A description of the various identified models is here given.

4.1 Glass melting furnace

For the furnace, models of different structures and orders were tested and subsequently compared by using appropriate performance indices. As models, three linear types were identified: i) AutoRegressive with eXogenous Input (ARX); ii) AutoRegressive Moving Average with exogenous Input (ARMAX); iii) State-space (SS) models with the standard N4SID subspace method. As performance indices, three well-established information criteria, that is, the Akaike, the corrected Akaike, and the Bayesian criterion (Armenise et al., 2018), and a percentage fit (PF) approach were used for the selection of the best model order. The PF is defined as:

$$PF = 100 \times \left(1 - \frac{1}{\overline{y}} \sqrt{\frac{1}{N} \sum_{k=0}^{N} (y_k - \hat{y}_k)^2} \right) \tag{1}$$

where y and $\hat{y}$ are the original and the model output, respectively, while $\overline{y}$ is the average of the original output, and N is the number of samples. To suitably merge the results of the various indices, a weighted scoring system of the Borda count type was used (Emerson, 2013). As an example, for the state-space models, the adopted scoring system indicated a model with $n = 7$ (i.e., number of states) as the best order.

Figures 5 and 6 show the output time trends of the best two input/output models and the best state-space model for the identification and the validation stage, respectively. The obtained models prove to give good results in terms of fitting on both datasets; only a limited decrease in performance is registered in validation. For all 7 outputs, corresponding PF are computed. As a matter of fact, for the selected SS model, the average PF reduces from 98.05% in identification to 94.56% in validation, which can be considered a good result. This effect appears less pronounced for the input/output models: in this case, the average PF in validation decreases to 96-97% for the best models, but non-optimal orders may produce unstable responses in validation. Note that for the SS models, a Kalman filter is also identified and then adopted in validation to limit the prediction error.

Furthermore, a consistency analysis was also performed on the SS models, aimed at evaluating their repeatability along the 3 selected datasets. As a compact metric to evaluate the obtained results, the average of the mean relative distances between the corresponding identified eigenvalues on the complex plane is calculated. As a result, this distance is equal to 0.0075, a value that can be considered reasonably small.

4.2 Control valves

For what concerns the control valves, simple ARX models with a reduced order were used, that is, 10 ARX(1,1) models, with one pole, no zero, and no time delay. As a compact metric, the average PF index over the 10 models was computed for both datasets; average PF reduces from 99.07% to 97.40%, which can be considered another good result. It is worth noting that the obtained models have a static gain equal to 1.05 ± 0.12 and a time constant equal to 12.5 ± 3.2 s, which is much smaller than the

Table 1. Average results of fitting for the identified controller parameters.

PF	Position form	Velocity form
ID	95.99	99.26
VAL	94.74	98.10

time constants of the furnace, which are instead around 1-2000 min. Therefore, the valve dynamics can be well neglected with respect to the furnace dynamics when the subsequent closed-loop simulations are performed.

4.3 PID controllers parameters

Finally, the parameters of 11 PI/PID controllers were identified. Since no information about the actual algorithm implemented in the plant PLC was available, two standard forms were tested and compared: position and velocity. After extensive tests, it was concluded that the various controllers were implemented online in the velocity form. As a compact metric, the PF index for the various tested models was computed for both datasets, identification (ID) and validation (VAL). To this aim, Table 1 limits to show the PF values averaged over the 11 identified models for the two tested algorithms.

5. MODEL-BASED CONTROLLERS

Once identified, the models were employed to compare two different control architectures, that is, a decentralized scheme comprised of SISO controllers and a centralized one with a model predictive controller (MPC). For both control schemes, as the furnace model, the best state-space model (with 7 states) was adopted. Corresponding closed-loop simulations were performed in MATLAB/Simulink.

5.1 Controller definition

The parameters of the SISO (PI/PID) controllers were firstly changed from the values obtained in the model identification stage with the routine plant data, as described in Section 4.3. In particular, a refined tuning was obtained with the PID Tuner app of MATLAB by maximizing the phase and gain margins of the closed loop functions to obtain small settling and rise times and limited overshoots. Being the identified model characterized by evident input-output interactions, some controller gains were further reduced to limit the negative effects between channels.

The MPC designed within the dedicated MATLAB toolbox has an offset-free formulation and is comprised of a Kalman Filter for the estimation of the state and disturbance, and a dynamic block with quadratic programming, which computes the optimal input to the process based on the model trajectory to the set-points. Note that this centralized controller directly manipulates the 10 gas flow rates, while the distribution logic described in Section 2.2 is implemented only for the decentralized scheme, but the valve dynamics are anyway neglected. Suitable constraints are thus imposed on the inputs, on the input rate of change, and on the outputs. Despite there is no explicit constraint on the methane/oxygen flow rate ratios, the MPC was verified to respect this specification. Further details (e.g., on tuning) are omitted for the sake of brevity.

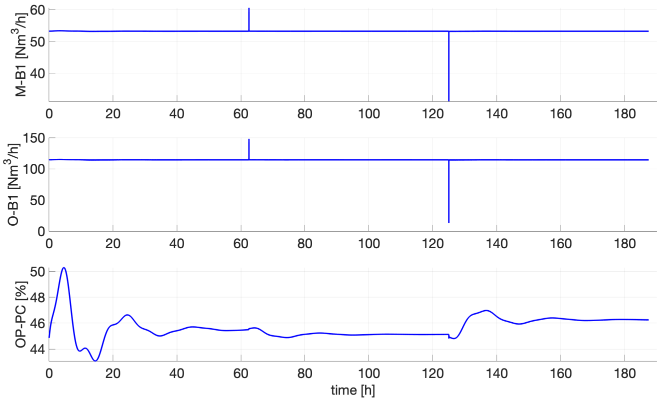

Fig. 7. Trends of MVs for the decentralized control scheme.

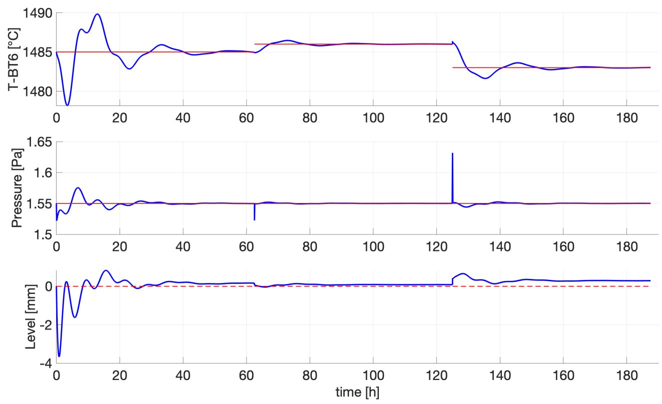

Fig. 8. Trends of CVs for the decentralized control scheme.

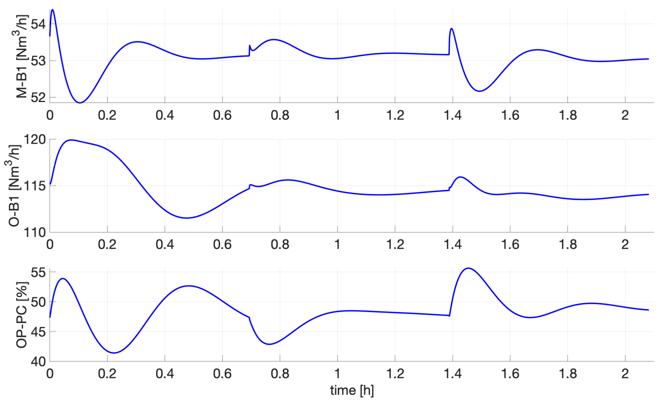

Fig. 9. Trends of MVs for the centralized scheme (MPC).

5.2 Controller comparison

A constant setpoint for the pressure is set (1.55 bar) and 2 step-wise changes (1485 → 1486 → 1483°C) are imposed to the temperature setpoint. Figures 7 and 9 show the time trends of 3 of the 11 manipulated variables (MV), for the decentralized control scheme and the MPC solution, respectively, that is, methane and oxygen flow rates from burner 1 (M-B1/O-B1), and the fan input command (OP-PC). Figures 8 and 10 show 3 of the 7 control variables (CV) (temperature of BT6, pressure, and molten glass level) for the two considered architectures. Note that the molten glass level has a zero set-point value which is tracked without acting on the corresponding manipulated variable, that is, the loading machine input command, since the identified model does not include this input variable. Note that obtained closed-loop time constants are

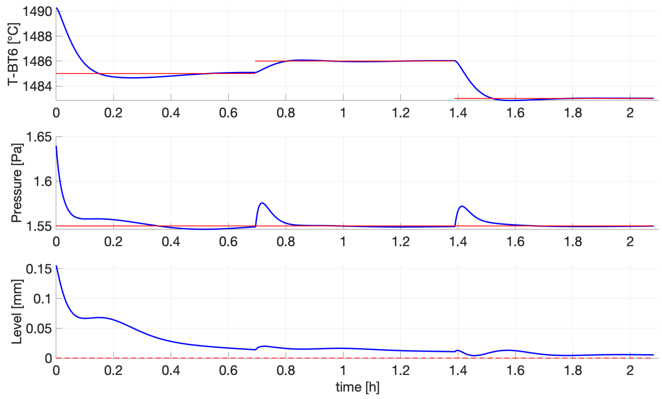

Fig. 10. Trends of CVs for the centralized scheme (MPC).

Table 2. Key performance indicators.

KPI	Decentralized scheme	MPC
$T_{sett}-1$ [min]	2645	16
$T_{sett}-2$ [min]	2627	17
IAE_T	379730	4004
IAE_P	1047	50
IAE_L	163440	797
TV_F	1596	214
TV_P	25	31

very different for the two compared controllers. Therefore, to best visualize the transient dynamics it is necessary to define different simulation spans, that is, one week for the decentralized scheme and just around two hours for the MPC solution. As a matter of fact, the setpoint tracking ability of the MPC is much superior; fast responses with limited oscillations are possible.

To perform a fair quantitative comparison between the two controllers, the same simulation span of one week is considered and some suitable key performance indicators (KPIs) are computed. In particular, the following metrics were used: the settling time (T_{sett}) in response to the considered variations (1 and 2) of the temperature setpoint; the Integral Absolute Error (IAE) on the three output variables (temperature, pressure, and level); the travel variation (TV) of manipulated variables, that is the overall flow rate of methane and oxygen (F) and the pressure (P). As an example, TV on P (TV_P) is computed as:

$$TV_P = \sum_{k=1}^{N} (P_k - P_{k-1}) \tag{2}$$

The different numerical values obtained for the KPIs are summarized in Table 2. It can be noticed how the KPIs confirm the observations made on the time trends. MPC outperforms the decentralized scheme since it can guarantee fast responses, that is, smaller settling times and limited oscillations on output and input variables; as a matter of fact, all three IAEs and TV_F are significantly reduced by MPC, while TV_P shows only a little increase.

6. CONCLUSIONS

Since the input raw materials entering the glass production plant have high variability, controlling the main variables of the melting process, such as temperature, pressure, and level, proves to be a major and challenging problem. To this aim, practical dynamic models have been derived to describe the behavior of the glass melting furnace with its main components and then pave the way for the implementation of an advanced control system. In particular, two different control architectures have been derived and compared: a decentralized PI/PID scheme and an advanced solution made of a predictive controller. The decentralized control allows only a slow setpoint tracking of temperature and pressure with significant oscillations, while major steady-state deviations are registered on the level. The MPC solution guarantees higher performance; setpoint tracking is indeed possible with fast responses and limited overshoots. In terms of performance indicators, this model-based solution yields lower settling times and smaller integral absolute errors as well as reduced travel variation of the manipulated variables. Future work will be devoted to building models for the second process stage, that is, the glass conditioning, as well as implementing the obtained models and controllers into the industrial PLC.

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